IEDE SPRING 2023 BIG DATA ANALYTICS TEAM

ARTIFICIAL INTELLIGENCE FOR DECISION MAKING IN THE ERA OF BIG DATA

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Abstract

Big data analytics has attracted significant attention from academicians and practitioners as it provides several ways to improve economic performance and efficiency. In the same line of thought, this study fosters performance, efficiency, and innovation through big data applications by focuses on big data and decision making in AI. The objectives are three folded. The first is to find out how big data has been used to enhance decision-making. The second one suggests the challenges big data non-users face when adopting big data. The last one recalls the implication of not incorporating big data as driven by decision-making. To map literature on big data and decision making, we use the Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols. The literature search is done to identify relevant research papers published between 2000 and 2022 in the comprehensive database of Web of Science, and Scopus. Big data users benefit from the AI advantages as big data act as assistance in decision making, as a result, it enhances knowledge, performance, efficiency, productivity, and give a hedge on competitiveness. As overall, big data users contribute to the digital economy. Yet there are challenges towards big data such as misunderstand, lack of top management commitment, lack of qualified and experienced consultants, lack of trust in data. Thus, a proper deal with challenges faced with big data should be adopted. This will help non users to adhere and users to become more confident towards big data. This will contribute in boosting digital technology as more sectors will get big data involved in their decision making and with time none will be left out regarding digital transformation.

Keywords: Big data, AI, Decision making, Users, Challenges

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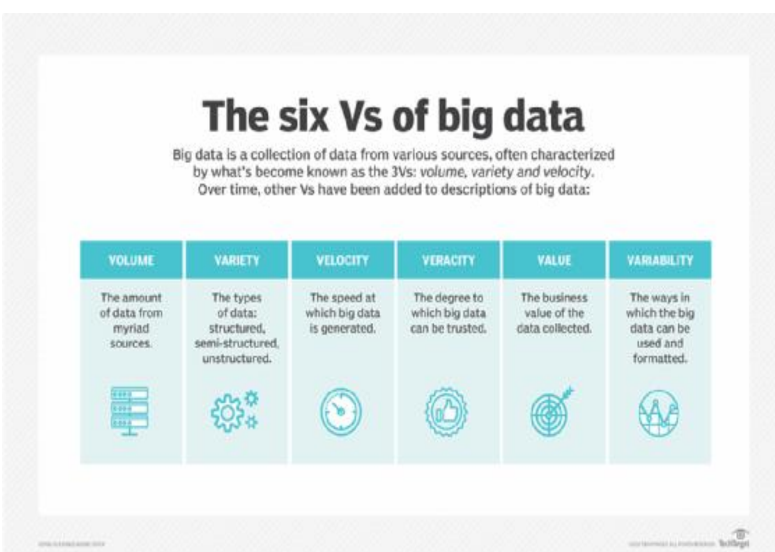
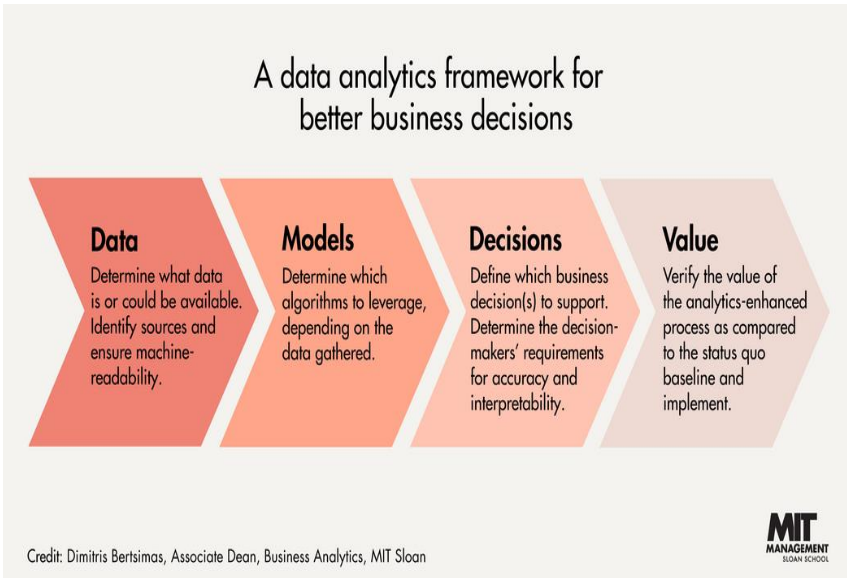
1. Introduction

We live in the era of big data, where governments, organizations, and marketers know, or can deduce, an increasing number of data items about aspects of our lives that, in previous eras, we could assume were reasonably private. Devices to capture, collect, store, and process data are becoming ever-cheaper and faster, while the computational power to handle these data continuously increases. Digital technologies have made possible the datafication of society, affecting all sectors and everyone's daily life. The growing importance of data for the economy and society is unquestionable, and more is to come (Da Bormida, 2022).



(Da Bormida, 2022) argue that from a more specific technical perspective, big data has five essential features. The first one is the volume which represents the size of the data, notably the quantity generated and stored. The volume of data determines its value and potential insight. To have big data, the volume has to be massive (Terabytes and Petabytes or more). The second one is variety, which describes the data's type and nature and how it is structured. Big data may draw from text, images, audio, and video (and data fusion can complete missing pieces) and be structured, semi-structured, or unstructured. Data can be obtained from many different sources (from social networks to in-house devices to smartphone GPS technology), whose importance varies depending on the nature of the analysis. Big data can also have many layers and be in different formats. The velocity is the time needed to generate and process information. Data have to flow quickly and in as close to real-time as possible because, indeed, in a business context, high speed can deliver a competitive advantage. Veracity has to do with data quality and reliability; it is essential to have ways of detecting and correcting any false, incorrect, or incomplete data. The analysis of reliable data adds value within and across disciplines and domains. Value arises from the development of actionable information.

Big data describes large amounts of data ineptly processed by conventional applications. Big data is a more extensive process; its tools are smart and complex. Unordered data are transformed into useful data sets using automation and parallel processing. Likewise, many computational and statistical procedures are used when evaluating and deciphering data. Big data isn't concerned with responding to specific questions; instead, it peruses enormous databases in sometimes irrational ways to reveal trends. Big data generates more significant thoughts that focus on what concerns should be addressed.



The explosion of large amounts of traffic data has guided data scientists to create models with big data for better decision-making. Big data applications process and analyze this massive amount of data (collected from various heterogeneous data sources) that cannot be processed with traditional technologies (Sbai & Krichen, 2020). Big data has received tremendous attention from managers in every industry, policy, government decision-makers, and researchers in many different areas (Zhan & Tan, 2018). The transformative power of today's big data has allowed many decision-makers to evolve unprecedentedly. Concerning decision-making, artificial intelligence (AI) takes task delegation to a new level. By employing AI-assisted tools, companies can provide their human resource departments with the means to manage the existing data and human resources altogether (Radonjić et al., 2022). Using AI for decision-making has been one of the essential applications in AI history. The roles of AI have been classified in various ways. AI systems can support, assist, or replace human decision-makers (Duan et al., 2019).

In recent years, decision-making for organizations and individuals has become more and more data-centric and analytics-based (Chen et al., 2021). Though frequently used, big data is usually associated with complex and large datasets on which special tools and methods are used to perform operations to derive meaningful information and support better decision-making. However, the big data concept is not just about the quantity of data available but also encompasses new ways of analyzing existing data and generating new knowledge (Da Bormida, 2022). Big data analytics guarantees that data may be analyzed and categorized into useful information for businesses and transformed into big data related-knowledge and efficient decision-making processes, thereby improving performance (Ferraris et al., 2019). The challenge is obtaining valuable information to help us make future decisions. Big data allows us to see history clearer, to get hidden values, and make the right decisions for the government and farmers (Chuluunsaikhan et al., 2019).

Big data analytics has attracted significant attention from academicians and practitioners alike as it provides several ways to improve strategic, tactical, and operational capabilities to positively impact organizations' economic performance and efficiency (Raut et al., 2021). In the same line of thought, this study evaluates the big data in assisting decision-makers in their decisions; thus, the objective of this study is three folded. The first is to find out how big data has been used to enhance decision-making. The second one suggests the challenges big data non-users face when adopting big data. The last one recalls the implication of not incorporating big data as driven by decision-makers. In the era of big data, significant data initiatives are critical for transforming traditional decision-makers into data-driven decision-makers, thus placing big data analytics at the top goals. Processes are being automated, which pledges to turn into a success. This study fosters performance, efficiency, and innovation through big data applications.

The following section focuses on the methodology, while the third is on the results section. The fourth one discusses the findings, and the last one concludes.

2. Methodology

2.1. The review protocol

The study protocol was developed using the Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) (Moher et al., 2009) to map literature on big data and decision making. The literature search was done to identify relevant papers published between January 2000 and March 2023 in the comprehensive database of Web of Science, and Scopus. Articles dealing with big data and decision making in AI were considered, particularly research papers. Following the PRISMA-P, the study protocol comprises four major sections: the search strategy, the selection criteria, quality assessment and data extraction. Each step includes other stages, such as identification, screening, eligibility, and inclusion as explained below.

2.2. The search strategy

We started the literature identification process by setting research objectives. We developed defined keywords and tailored them to two digital databases namely, Web of Science and Scopus. Designing a comprehensive and relevant set of keywords is key to the quality of the Systematic Literature Review data. To fulfil this goal, we enriched the set of keywords in each subsequent round based on the results returned from both databases in the previous round. We used nine rounds of keywords, followed by reviewing contents and adding alternative keywords to the evolving library, then applying the following Boolean search.

Table 1. Keywords search

Rounds	Keywords
1	'Artificial intelligence' AND 'big data' AND 'decision-making'
2	AI AND bulk data AND managing
3	Robotics AND large data volumes AND directing
4	Expert systems AND large databases AND governing
5	Big data AND decision making AND penetration OR entrance OR invasion OR insertion
6	Big data AND decision making AND usage OR practice OR use OR acceptance
7	Big data AND decision making AND challenge OR barriers OR Obstacles OR problems
8	Big data AND decision making AND implication OR meaning OR involvement OR significance
9	Big data AND decision making AND Innovation OR Newness OR Latest things OR addition

2.3. The selection criteria

The process involves setting the inclusion and exclusion criteria (Moher et al., 2009). The search focused on mapping existing literature in various sectors. All searches include only research papers published in English. Papers found include case studies, surveys, secondary data, and mixed approaches. The selection criteria were opened to all sectors. Below is the summary of our search criteria:

- Research articles published from January 2000 to March 2023
- Research articles related to the field of study
- Research articles related to the research objective
- Research articles fully in English

Any article not aligned to the above criteria has been exclude.

2.4. The quality assessment

With the defined selection criteria and search strategy, the initial keywords search ended with 2000 papers. We removed 54 duplicates papers, followed by abstract, reading and checking of title to ensure that articles remain purposeful to the study objectives. We had 1844 non-related and 5 papers without full access removed. A full-text reading was done, and 56 articles were excluded. During the last stage of the quality assessment process, a horizontal and vertical check was done by matching the content of the remaining articles to the themes of the study. Thus, a total of 41 research articles were selected for the study. Figure 1 shows the summary.

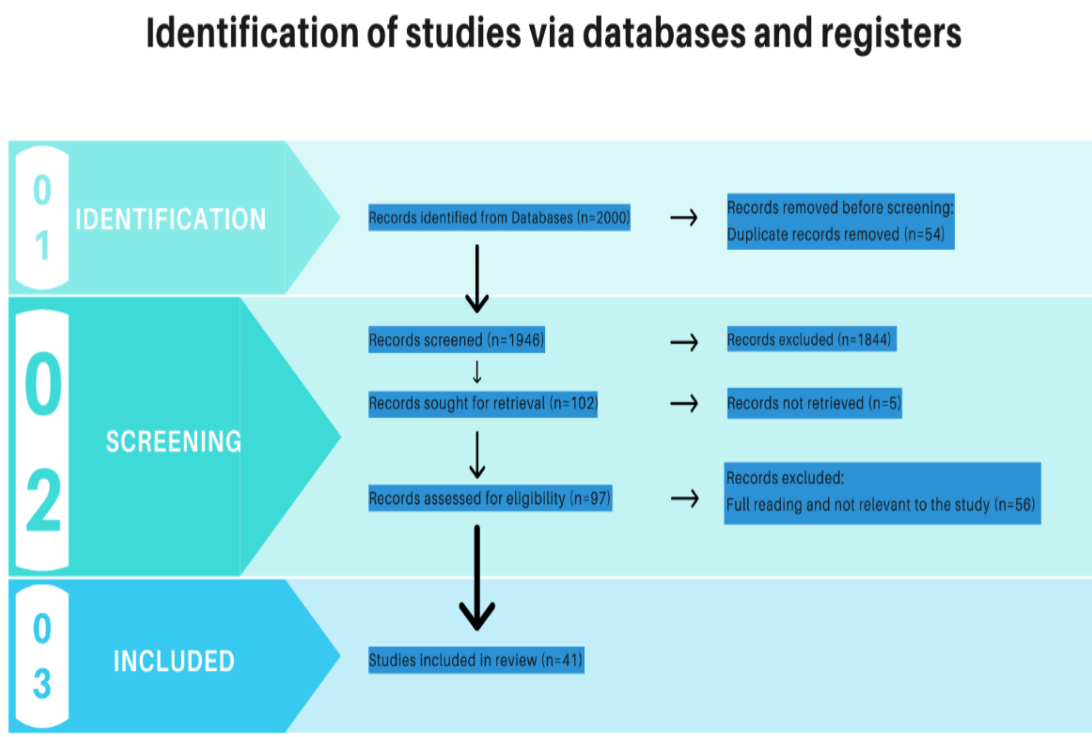


Figure 1. The review process using PRISMA-Protocols

2.5. The data extraction

The excel sheet application was used to extract essential information about the 41 selected papers. The extracted details include the names of author(s), digital object identifier (DOI) of the paper, research methodology, article type, article title, date of publication and source description (country-specific or global context).

3. Results

3.1. Distribution of papers published over time

The overall results in Figure 2 showed a trend of volatility in publication. That is from 2000 to 2015, no literature was found. However, the trend started growing from the year 2016 with 1 publication, and the highest number of publications in 2021 (15 papers) followed in 2019 (10 papers). The result implies a gap in the literature, and thus research in this field is still in its infancy. On the other hand, it suggests a positive trend and alignment with the rising global concern and interest in big data and decision making in AI during the last 7 years.

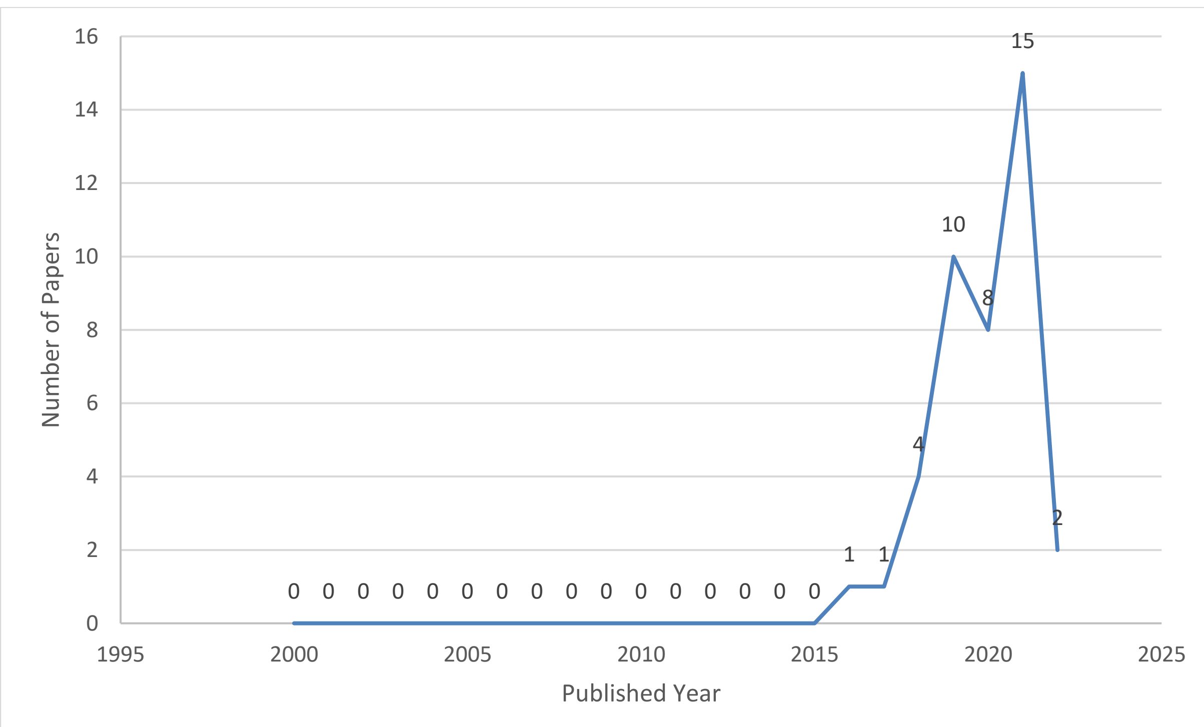


Figure 2. The distribution of papers published over time

3.2. Distribution of articles by journals

We examined the number of publications made by journals and evaluated their influence and audience in this field. The overall analysis of published articles listed in Table 2 showed that the journal, Technological Forecasting and Social Change had 7 publications, followed by International Journal of Information Management with 3 publications. Whereas 6 journals had 2 publications each and the remaining journals have 1 publication each. Therefore, a total of 41 reviewed articles were published by 27 different international journals across various sectors. This result suggests much relevance of the topic to different academic fields and for policy makers.

3.3. Representation of research approach

We purposively analyzed the kind of research carried out in this field to help comprehend why there are limited studies. The results in Figure 3 showed that empirical studies have a more significant influence on the overall publications, as it's account for 100%. With the survey accounting for 56%, followed by case study and secondary with 20% each. The last one which is the Mixed is 4%. The result suggests more qualitative studies over quantitative studies and few case study studies compared to the mixed ones.

3.4. Representation of research by sectors

During the last 7 years, researcher have shown interest in studies on big data and decision making, as a result Figure 4 presents the various sectors involved in big data while making decision. Research have been done most in diverse sectors and account 32%. manufacturing is second with 27%. Then comes the health sector with 10%. transportation, retail and finance are 7% each. Education is 5% while government, agriculture and food services are 2% each. None relevant studies are on energy and telecom.

3.5. Author and co-authorship analysis

We conducted author and co-authorship analysis to reveal the works and networks that exist among researchers. The overall results showed that 100% of the papers were co-authored. Our institutional affiliation analysis from Table 3 shows that United Kingdom, China, and India have more affiliated institutions with 29, 28, and 12 papers, respectively. This suggests that institutions are developing more interest in decision making using big data in AI.

Table 2. Distribution of reviewed articles

Serial Number	Name of Journals	Number of Papers	Published Year
1	BMJ Open	1	2018
2	Business Process Management Journal	2	2019, 2021
3	Cities: The International Journal of Urban Policy and Planning	1	2021
4	Computers in Human Behavior	1	2021
5	Computers in Industry	1	2021
6	Ear and Hearing	1	2020
7	Economics of Innovation and New Technology	1	2018
8	European Journal of Operational Research	1	2018
9	European Management Journal	1	2022
10	Industrial Management and Data Systems	2	2019, 2021
11	Information and Management	1	2019
12	Information Processing and Management	1	2021
13	Interactive Learning Environments	1	2019
14	International Journal of Information Management	3	2018, 2019, 2020
15	International Journal of Logistics Management	1	2021
16	Journal of Asian Finance, Economics and Business	1	2020
17	Journal of Business Research	2	2016, 2019
18	Journal of Enterprise Information Management	2	2020, 2021
19	Journal of Multimedia Information System	1	2019
20	Management Decision	2	2019, 2020
21	Procedia CIRP	1	2019
22	Procedia Computer Science	2	2017, 2020
23	Resources, Conservation and Recycling	1	2019
24	South African Computer Journal	1	2021
25	Technological Forecasting and Social Change	7	2020, 2021
26	Tourism Management	1	2022
27	Transport Policy	1	2020

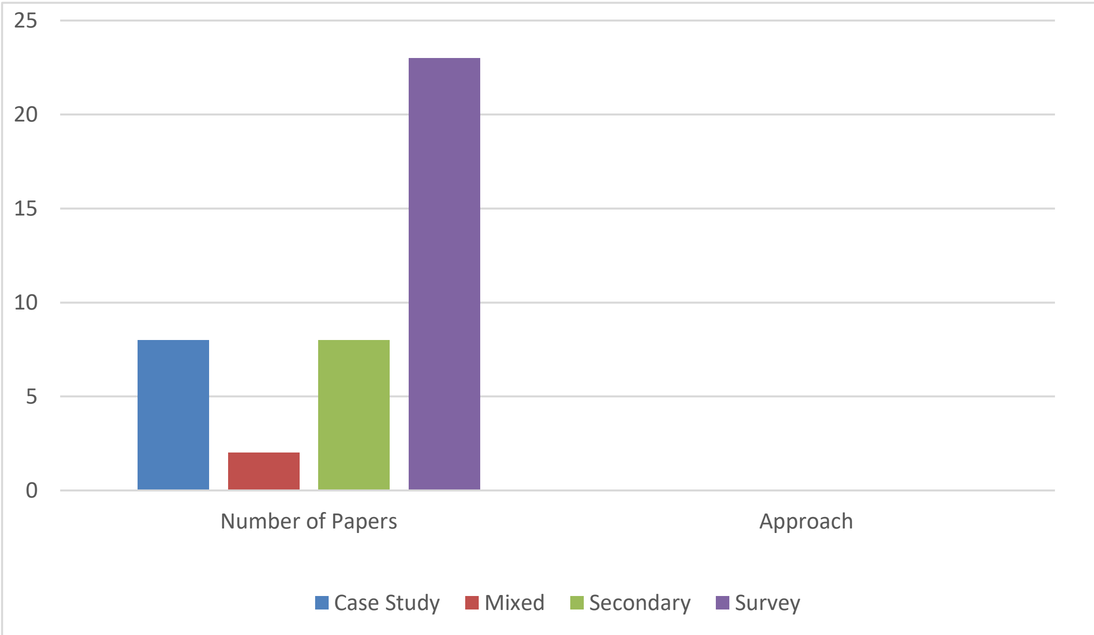


Figure 3. Representation of research approach

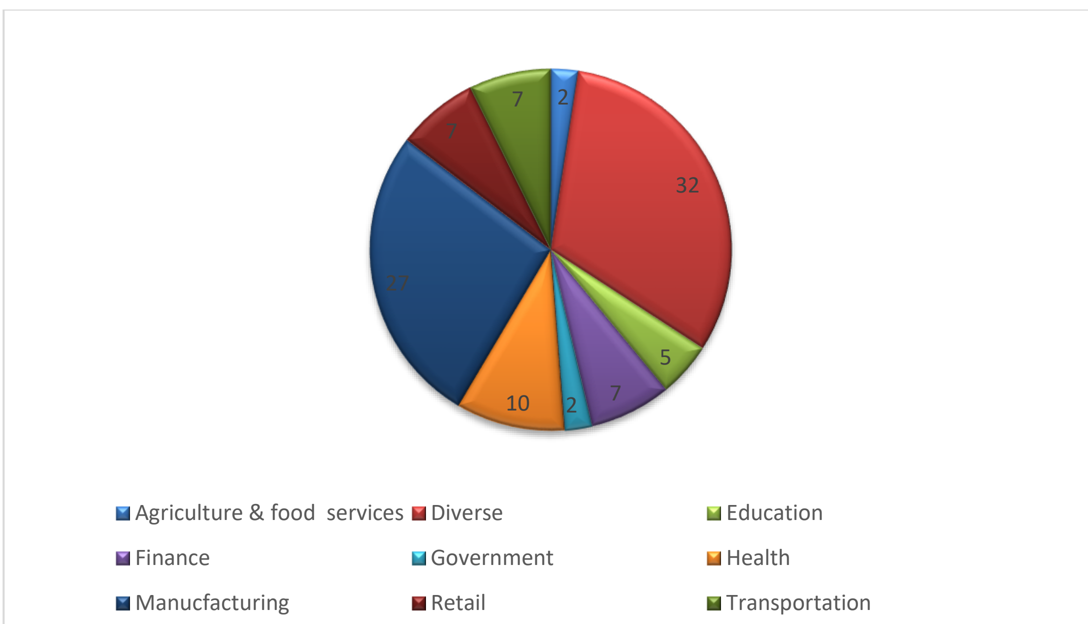


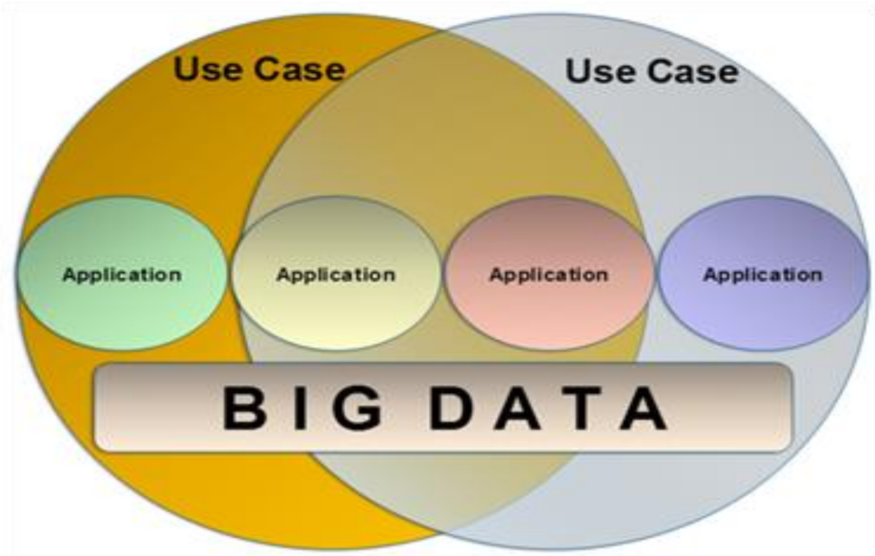
Figure 4. Representation of articles by sectors

Table 3. Affiliation of authors

Affiliations	Number of authors
United Kingdom	29
China	28
India	12
Denmark	11
New Zealand	7
Pakistan	7
Portugal	6
Australia	5
Germany	5
Italy	5
Korea	5
South Africa	5
United Arab Emirates	5
United States	5
Brazil	4
Czech Republic	4
France	4
Turkey	4
Greece	3
Malaysia	3
United Kingdom	3
Canada	2
Finland	2
Kingdom of Saudi Arabia	2
Morocco	2
Tunisia	2
Bangladesh	1
Cyprus	1
Hong Kong	1
Russian	1
Spain	1
Switzerland	1

4. Findings

4.1. Users



The literature has identified several sectors for using big data in decision-making. We describe how those sectors use big data in making decisions.

Big data for decision-making purposes is used in the automobile component manufacturing industry in three groups: purchasing, manufacturing, and logistics & marketing, among which the best big data-driven circular economy is manufacturing (Kamble et al., 2021). Big data is also used in a framework manner to solve an optimization problem. Dynamic vehicle routing problem in a decision support system shows that the proposed architecture improved due to its capacity to cope with big data optimization problems by interconnecting components and deploying on different cluster nodes (Sbai & Krichen, 2020). 199 Spanish service countries strongly affect the facilitating conditions on the intention and use of big data. To overcome the challenge of obtaining valuable information and making future decisions, an agriculture big data analysis system is developed and consists of agricultural big data collection, big data analysis, and big data visualization (Chuluunsaikhan et al., 2019).

Big data enhances supply chain performance (Zhan & Tan, 2018). Big data supports public health policy decision-making for hearing (Saunders et al., 2020). Companies employ big data to provide their human resource departments with the means to manage the existing data and human resources altogether (Radonjić et al., 2022). Big data is used to assess business value in European firms, and results show that big data analytics can provide business value to several value chain stages. Big data analysis can create organizational agility through knowledge management and its impact on the process and competitive advantage (Côrte-Real et al., 2016). Big data is used on firms' innovation performance. Big data's main characteristics, such as volume, variety, and velocity, can impact firms' innovation efficacy and efficiency. And results confirm that data variety and velocity positively enhance firm innovation performance, with velocity playing a more important role in improving firm innovation performance. In contrast, data volume has no significant impact; that is, data volume does not play a critical role in enhancing firm innovation performance (Ghasemaghaei & Calic, 2019).

Big data can be used on firms' innovative performance in terms of product innovations. Since big data technologies provide new data information practices, they create novel decision-making possibilities widely believed to support firms' innovation process. Applying German firm-level data within a knowledge production function framework, evidence suggests that big data analytics is a relevant determinant for the likelihood of a firm becoming a product innovator and for the market success of product innovations. These results hold for the manufacturing and service sectors but are contingent on firms' investment in IT-specific skills. Overall, the results support the view that big data analytics have the potential to enable innovation (Niebel et al., 2018). Big data can sustain textile manufacturing in developing countries (Hack-Polay et al., 2020). Big data can be used to enhance sustainable supply chain performance. Big data analytics talent capabilities significantly affect employee development and sustainable supply chain outcomes (Bag et al., 2021). Big data measures firms' performance and knowledge management. And it is shown that firms that developed more big data analytics capabilities than others, both technological and managerial, increased their performances and that knowledge management orientation plays a significant role in amplifying the effect of big data analytics capabilities (Ferraris et al., 2019).

In China, big data is also used to measure emerging market firms' performance, support decision-making among emerging market firms, and enhance their performance

(Saqib Shamim et al., 2020). Big data boost circular economy performance, demonstrating that big data analytics capability drives decision-making quality in organizations. Data-driven insights do not mediate this relationship which offers important insights to managers. They can act as a reference point for developing data-driven insights with the circular economy paradigm in organizations (Awan et al., 2021). Big data improve higher education institutions' performance in Malaysian as results revealed that data-driven decision-making could positively play an essential role in the relationship between big data analytic capability and the performance of higher education institutions (Ashaari et al., 2021). Big data can create value for clinical decision-making by enhancing policy in New Zealand (Weerasinghe et al., 2021). Big data build the competitive intelligence of organizations. The competitive intelligence process includes monitoring competitors to deliver actionable and meaningful intelligence to organizations (Ranjan & Foropon, 2020).

Big data is also used in emerging market firms for innovation in an open economy such as China, and findings show that international diversification and related business diversification positively improve firms' innovation performance. In contrast, overall business diversification negatively impacts firms' innovation. International and business diversification substitute for each other to affect firms' innovation outcomes. Further research found that these results are more significant in a higher big data development environment (Xie et al., 2021). Big data also encourages better risk management (Battisti et al., 2019). Big data is also used to support the data-driven decision-making process in the banking sectors in South Africa (Pillay and Merwe, 2021). Big data is also used for decision-making in chemical enterprises (Zhang et al., 2019). Big data is used for decision-making in Chinese public and private hospitals. It is revealed that data management challenges (leadership focus, talent management, technology, and organizational culture for big data) are significant antecedents for big data decision-making capabilities in both public and private hospitals. Moreover, it was also found that big data decision-making capabilities played a crucial role in improving the decision-making quality (effectiveness and efficiency), positively contributing to environmental performance in public and private hospitals in China (Nisar et al., 2020).

Big data plays a role in management capabilities in the hospitality sector. Big data management capabilities lead to high online quality ratings by mediating knowledge creation and service innovation (Saqib Shamim et al., 2021). Big data helps information technology managers make decisions in smaller organizations which are significantly more likely to base their decisions on analytic results than managers in large organizations (Thirathon et al., 2017). Big data is used in the fashion industry for knowledge co-creation (Acharya et al., 2018). Big data helps emerging markets that employ many decision-makers intending to create a circular economy (Modgil et al., 2021). Big data validate public health policy-making platforms for hearing loss in UK and Denmark (Dritsakis et al., 2018). Big data is a tool in competitive scenarios (Contreras Pinochet et al., 2021). Big data can validate public policy in Denmark in the potential of textual in transportation (Kinra et al., 2020). Big data recognizes customers' real sentiments in Saudi Arabia's Financial Sector (Park & Javed, 2020). Big data helps improve remanufacturing performance (Bag et al., 2021). Big data help to make informed decisions for designing effective digital educational games (Liu et al., 2019). Big data increases smart organizational effectiveness in organizations (Niu et al., 2021).

From Chinese firms' perspective, big data can help to respond to market turbulence (Sheng et al., 2021). Big data enhances decision-making capability and quality among Chinese firms. Findings suggest that big data management challenges are the key antecedents of big data decision-making capability. Furthermore, the latter is vital for big data decision-making quality (S. Shamim et al., 2019). Big data is used to satisfy a customer in the beauty premium of tour guides (Yang et al., 2022). Big data can help successfully develop a new product (Aljumah et al., 2021). Big data helped control the spread of COVID-19 in Chinese urban cities through information and communication technologies such as health QR code (Guo et al., 2021).

4.2. Challenges

According to the literature, no studies discuss challenges faced while using big data to make a decision. Still, available studies are on challenges faced in implementing big data for decision-making.

4.2.1 Challenges linked to human resources

In their study, (Radonjić et al., 2022) argue that there are challenges in implementing big data in companies related to human resources managers. One of them is that it involves a vast amount of data structuring and that decision-makers must collaborate with the right data scientists to interpret the data they collect. While big data can be obtained from within and without the company, thus providing a multi-faceted insight into worker behavior, on the other, it implies a challenge in terms of its extraction, relevance, exploitation, and management. Businesses are collecting more data than they know what to do with. The challenge for decision-makers, therefore, resides in acquiring the skills necessary to extract from big data what is of most value to them and exploit it.

For the same reason, they should be able to identify its relevance in line with the benefits of AI and the challenges in its implementation. In terms of the challenges related to implementation, human resources managers first observe that AI facilitates the governance of big data. Yet, as a consequence, data structuring becomes a big issue. Next, human resources managers believe that while AI augments decision-making processes, the underlying risk is ill-suited implementation, which could provoke costs greater than the implementation itself.

Consequently, they note that AI and human resources converge regarding decision-making and data science. In other words, whereas data science gives the power to extract valuable information, human resources managers need to cooperate closely with data engineers to combine knowledge with strategy. This is simultaneously one of the greatest challenges elaborated in the theoretical part and perhaps one that encapsulates the entire AI and human resources relationship. Lastly, one of the greatest advantages of AI is that it enables cognitive and technological upskilling among decision-makers and all other workforce tiers. Simultaneously, however, due to the evolving nature of disruptive technologies and the need for technological competence, this is also the source of one of the greatest fears of job displacements.

4.2.2 Challenges linked to artificial intelligence

(Duan et al., 2019) mention that misunderstanding the term AI is a challenge in implementing big data for decision-making. AI has been applied in many domains, and numerous terms describe AI-based systems for decision-making, such as expert systems, knowledge-based systems, smart decision support systems, smart software agent systems, smart executive systems, etc. However, as AI constantly evolves and advances, the names of AI-based systems for decision-making have changed over the years. Many names for AI-based decision systems have disappeared or been replaced with new ones. It can be argued that defining AI and its related terms has become a moving target. To clarify any conceptual confusion and controversy, there is a need to systematically review AI-related definitions and terms and redefine them to reflect the new generation of AI in the era of Big Data.

Another challenge is the lack of measuring the benefit of AI and its impact. With the rapid increase in AI applications, many claims are made by AI developers and large corporates about its substantial benefits and impact. As most similar claims are not substantiated by measurable empirical evidence and rigorous academic research, it isn't easy to know how, why, and to what extent AI systems are being used, impacting individual and organizational decision-making and transforming organizations. This raises a challenge in measuring the benefits and impact of AI for decision-making from short to long-term and from social, economic, and political perspectives. The lack of understanding of AI and its impact on decision-making is also challenging. An appropriate theoretical framework should be developed to understand how and why AI-based systems affect individual and organizational performance.

The role of AI in decision-making is, again, a challenge. There has been an increased interest in examining the role of AI in recent years, i.e., automation or augmentation. Some AI practitioners and researchers argue that AI should augment human judgment rather than automation and that AI systems should be designed to augment, not replace human contributions. Still, this assertion should be further supported with rigorous research and investigation with empirical evidence on how and why AI is best at providing augmentation in supporting human judgment rather than decision automation. Many previous studies have examined the roles of AI before the era of big data. However, considering the superpower of the new generation of AI and the overwhelmingly mixed views and debate on the part of AI in decision-making, the role of AI must be revisited and redefined.

Another challenge lies in the system design criteria for supporting decision-making. As the effectiveness of AI systems for decision-making can only be realized through their acceptance and use by the end users, the system design criteria for AI-based systems have been an issue since the early applications of AI. Based on understanding the roles of AI, whether for supporting, augmenting, replacing, or automating decision-making, information system researchers need to propose the design criteria from the technology-human interaction perspective for system developers. This will create ideal AI systems for human decision-makers.

Refining and improving AI system performance while in use by decision-makers sounds difficult. The unique strength of human intelligence is its ability to learn and adapt to new environments and challenges. Refining and improving performance through continuous learning has been a challenge for advancing AI until the recent advances in big data.

AI users' behavior issues also count. Why do human decision-makers accept/reject using AI for decision-making? Previous research shows that when people use AI as a supporting tool for decision-making, different people may take different attitudes and actions on implementing the decisions the AI system recommends. For example, identifying the need for employees to adapt to the smart machines used to partially or fully automate cognitive work. Help people renegotiate their relationship with machines and to co-exist with smart machines by aligning their contributions in the age of AI. Senior managers' attitudes towards using AI can be critical as scaling AI in the enterprise demands new ways to engage business experts with technology.

Understanding the critical success factors affecting AI for decision-making is also a challenge. AI has been revitalized with big data and is becoming ever more powerful than before. However, while technological advancement may be unlimited, its applications may encounter bottlenecks and unprecedented barriers. Although many factors may affect the success of AI applications, it is important to identify the most critical success factors based on the empirical evidence collected from real-world AI applications. These essential success factors will help organizations focus more on addressing the most critical issues. The crucial elements of success can also offer valuable guidelines for AI designers and developers to overcome challenges and provide decision-makers with the most effective and acceptable systems.

There is a lack of understanding of the synergy of AI and big data. It can be argued that big data has empowered AI for its current boom, and the domain of cognitive computing will be incomplete without harnessing the benefits of big data analytics. The big data era has added data types not previously used in the analysis, such as social media. AI makes big data meaningful through cognitive computing because analysis of big data by humans can be highly time-consuming. Thus, using AI techniques helps make sense of big data. Yet AI is only one of many ways big data can be used. Therefore, a strong need exists to explore and understand the synergy of AI and big data. More research is needed to establish the unique advantages of combining these technologies and understand how AI can be further improved with the increasing availability of big data with its volume, variety, and velocity.

Culture, personal values, and AI applications matter as well. Culture has been recognized as an important, influential factor in technology acceptance by many studies in the past. Does culture, such as national or organizational culture and personal and religious values, also play a critical role in the acceptance/adoption and use of AI applications? For example, "Why Chinese companies approach AI differently" was examined. It also found a significant influence of organizational and Chinese national culture on knowledge management. If culture does play a role, how, why, and to what extent does it affect AI success? Furthermore, will the wide use of AI to support and automate human decision-making change culture?

Ethical and legal issues again matter. Rapid advances in AI are raising severe ethical concerns. Ethical and legal concerns surrounding the applications of AI have become a major challenge. This topic has received substantial attention and debate, so that a separate full paper would be more appropriate. However, as the role of government is critical for addressing the ethical concerns and legal challenges, particularly around responsibility for and explain ability of decisions made by an automaton AI system, more research must be carried out on the role of the government in shaping the future of AI. How can the government develop adequate policy, regulations, ethical guidance, and legal framework to prevent the misuse of AI and its potentially disastrous consequences on both individual and societal levels?

4.2.3 Challenges linked to organizations, individuals, and technology

(Li et al., 2019) identify a comprehensive set of barriers affecting the implementation of big data solutions in smart factory and divide them into individual, organizational, and technological categories.

Under the organization-wide barriers, we can count a lack of understanding and strategic planning. Lack of understanding and strategic planning is a common barrier faced by user companies when adopting new information technologies and systems. This barrier refers to a general lack of knowledge and understanding of smart factory and big data tools. As such, managers and practitioners often may neither envision related technical and business development strategically nor plan the whole implementation project properly.

Managers and users in the industry often experienced difficulties in understanding big data solutions, and so could not make proper strategic plans for these innovation projects.

Further, it is identified that several reasons cause this barrier. First, a smart factory is a new and highly complex concept, covering a variety of technical components that fall into the areas of electronic engineering, automatic control, telecommunication, and software engineering. Business managers and in-house information technology software experts "often do not have the multidisciplinary knowledge needed to develop a holistic smart factory development plan." Moreover, unlike a typical information system implementation project that often has a single vendor providing the system as a package, building a smart factory always involves multiple vendors. Those who, respectively, supply the needed central processing system systems, manufacturing execution systems, and big data analytics applications. This raises further challenges for "strategic planning, coordination and inter-organizational collaboration in smart factory initiatives."

Furthermore, it can take 5-10 years for a sizeable manufacturing company to be transformed into a truly smart manufacturing unit. And this will need to be done in stages, from basic digitalization at the shopfloor level to full automation and optimization of the entire manufacturing firm through big data solutions. In other words, big data analytics is an important component but will only be practically adopted in the later stages of the smart factory development cycle. This makes it even more difficult for manufacturing companies to develop a clear and suitable big data implementation plan when they are mainly at the early stage of the smart factory journey.

This lack of understanding and strategic planning, in turn, triggers the appearance of other organization-wide barriers (including lack of top management commitment and failure to identify big data analytical needs in smart factory). As further discussed below, People-related barriers (e.g., lack of trust in big data analysis results and user resistance) and technical and data barriers (e.g., poor big data management and increasing information security threats).

Another organizational barrier is the lack of top management commitment. Top management commitment and support have been widely recognized and well-reported as key factors affecting the information system implementation's success. Undoubtedly, in the context of a smart factory, top management commitment will still be crucial to allocate sufficient resources to related technical innovations and resolve potential user resistance and internal conflicts. Previous research reinforced that top management support and commitment will also be important to ensure big data sets. Often distributed across different geographical areas and owned by multiple internal and external units. They are appropriately accessed, collected, analyzed, and managed. However, due to a lack of understanding of big data and smart factory, top managers may be unable to envision the full benefits and usage of big data across the product lifecycle in an Industry 4.0 environment.

Consequently, they may only be willing to adopt some basic analytical functions related to production automation. Still, they could be less inclined to invest substantially in embedding a complete big data solution in their developing smart factory. Also, due to a lack of strategic planning, top managers may often fail to provide appropriate support at the right stage and right time to facilitate the implementation and usage of specific big data functions across the entire product lifecycle in a smart factory.

The third one is the lack of collaboration and alignment among organizational departments. In industry 4.0, big data exists in the production department and all other units in the product lifecycle, including sales, logistics, product research, purchasing, and after-sales service. A holistic, big data solution embedded in a smart factory will thus affect all functional areas of the product lifecycle. It will also require the cross-departmental collaboration of all units concerned. However, problems like competition for resources, contradicted goals, conflicted interests, and disagreements can always exist between organizational departments. As a result, a lack of departmental collaboration and alignment has been frequently reported as a crucial barrier leading to failure in enterprise-wide information system implementation.

Under people barriers, we have a lack of qualified and experienced consultants. External information system consultants play a crucial role in ensuring the success of information system development and implementation projects. These high-level information system professionals will generally possess multiple skills, including functional, technical, and interpersonal skills. Given the technical and business complexity of smart factory and big data, consultants needed in these implementation projects will be required to have even more insights and skills than usual. To meet the requirements of applying big data solutions in developing a smart factory, consultants must have technical knowledge of the resolution. They also and deep insights into how this big data tool can be applied to deal with specific user needs in a particular business and production context. Usually, high-skilled information system consultants are a valuable asset in the information technology industry and thus can be difficult to recruit and retain. Considering the level of project complexity and the fact that big data and industry 4.0 are relatively new concepts, finding and keeping suitable consultants with the needed experience and skills to implement big data solutions in the smart factory is currently very challenging for information technology companies. Due to a shortage of qualified and experienced consultants, manufacturing companies can face many challenges when applying big data analytics in their industry 4.0 initiatives. Organizations cannot easily link big data analytics with their business needs without sufficient support from external consultants. It is also difficult for them to realize the solution's full potential and receive proper user training.

Another people barrier is the lack of in-house data scientists. With the development and implementation of big data solutions, there has been an increasing demand for data scientists in organizations. A highly qualified and experienced data scientist can seamlessly bridge users and their requirements with big data tools and help transform the collected data into meaningful insights and reliable business predictions to support decision-making. However, manufacturing companies often find recruiting qualified in-house data scientists from the current job market difficult. Retaining them could be even more difficult due to an industrial shortage and high demand for this type of professional. Historically, external information system consultants and internal experts need to work collaboratively to provide training to key users and ensure the right people have the right skills and knowledge to operate the new system properly. However, in implementing big data solutions in smart factories, a lack of external consultants and internal data scientists will often make it difficult to deliver training to targeted user groups with suitable methods and content. This lack of user training can, in turn, lead to other people-related problems within smart factories. e.g., lack of trust in the results of big data analytics as well as user resistance towards changes initiated by big data analytics and smart automation, as further discussed below.

The third challenge is the lack of trust in big data analytical results. When big data is receiving increasing attention from business managers, it is essential to consider whether the analytical results generated by big data solutions can be trusted. It is argued that big data may compromise too many interests in a company and can even lead to different individuals finding supporting evidence for any argument they favor. In light of this discussion, practitioners may doubt whether big data analytical results can make decision-making more efficient or lead to confusion and potential conflicts. But the value and accuracy of big data analytical results inevitably depend on the quality of the original data sets. However, the lack of an integrated and consistent data set was found to be a common problem in manufacturing companies.

Consequently, business managers may make decisions based on their experience and intuition rather than on unreliable or inaccurate results suggested and predicted by new analytical tools. Also, owing to a lack of understanding, planning, and training, some users in manufacturing companies may be less inclined to trust, accept and use big data tools even if the related analytical results can, in essence, be useful to support their decision making. In this case, the full power of big data analytics will be greatly underutilized.

Another one is user resistance caused by job roles and skills changes. User resistance is a typical and, in fact, inevitable phenomenon during the implementation of enterprise-wide information systems, which will substantially change the company's status quo and take people out of their comfort zone. In a smart factory, production automation enabled by innovative technologies will dramatically reduce manpower. Companies no longer need to dedicate people to oversee the operation of machines, as central processing systems can achieve self-operation, self-monitoring, and even self-maintenance. Adopting big data solutions in a smart factory will extend a degree of automation and changes from the production unit to other business divisions (e.g., sales, logistics, purchasing, and after-sales services) across the product lifecycle. These changes and the potential fear of job loss can lead to solid user resistance towards big data and smart factory development. There will always be a reluctance to change, which is natural because you get people out of their comfort zone by engaging them in a different operational environment and requiring them to have a whole new set of skills.

Under the technical and data barriers, an immature central processing system and the internet of things development exist. A highly efficient internet of things infrastructure composed of sensors and a central processing system provides the foundation of smart automation. Thus, companies generally consider central processing systems and internet of things sensing infrastructure the first important milestone to be achieved in developing smart factories. However, given the cost and technical complexity of transforming existing manufacturing equipment and production lines into a fully automated central processing system, this milestone cannot be achieved easily. The problem of the immature central processing system and internet of things development will not just lead to data fragmentation and inconsistency. Still, it can also raise potential information security threats, which will, in turn, affect the implementation and usage of big data solutions in smart factories.

Another technical barrier is the lack of an integrated and consistent big data set. Big data of a smart factory can be collected from various internal and external sources, including machine sensors, management information systems, social media platforms, and the internet. Such data are big in volume and contain very different forms and formats, e.g., signals, texts, graphs, photos, videos, and audio. Before data analysis, these big data sets must be properly collected, processed, and cleaned to ensure high accuracy, integrity, and consistency. Otherwise, big data solutions cannot produce accurate, meaningful analytical results and predictions supporting automated production and business decision-making. Data quality is a key determinant of the success of any big data initiative in smart factories. We need to generate consistent and complete datasets before trying to exploit them. The rule is garbage in, garbage out. Only top-quality data can ensure top-quality data analytical outputs. However, due to big data sets' volume, complexity, and diversity, it can often be challenging for smart factories to maintain high data integrity and consistency. Historically, inaccurate, inconsistent, and redundant data may exist in management information systems due to inappropriate system usage and maintenance. The situation of a smart factory is even more complicated, as human errors, immature central processing systems, and internet of things development can cause data quality problems.

4.2.4 Challenges linked to tradition, culture, and education

(Hack-Polay et al., 2020) mention some points hindering decision-making vis-a-vis big data application in textile manufacturing. The first one is the traditional and cultural aspects of decision-making in developing countries. In an Asian context, the leader-member exchange is not singular, meaning it does not extend only to workplace relationships. But the leader-member exchange in vertical-collectivistic spheres is multi-dimensional, which signifies that relationships between leader and followers stretch beyond organizational boundaries. These then enter the arena of social exchange and involve subjective and emotive domains such as effect, contribution, and allegiance or loyalty. In this perspective, in the highly vertical-collectivistic societies of Southeast Asia, decision-making regarding strategy, particularly investment in new technologies such as biotechnologies, rests mainly with the elders (who also own the capital and means of production). The cultural issue is intertwined with other critical issues, that of generations and education.

The other point is on generation conflict and education. Most textile plant owners in Southeast Asia are among the Baby Boomer generation (1946–1964). They felt the hardship in the aftermath of the war and developed an economic ethos centered on economic rationality. The economic and political choices made by Baby Boomers have been fiercely criticized by Millennials (the next generation). The main charge is that Baby Boomers wretched the economy and made political decisions that disadvantaged Millennials who inherited dysfunctional economic systems and international relations. However, these views are challenged by others. Regardless of the blame game, the reality of the generation conflict is tangible and ongoing. The potency of this conflict is exacerbated in the vertical-collectivistic context of Asian culture because it is a cultural vice to challenge the elders.

The second issue of contention is education. By education, we do not imply only schooling and training; our perspective on education encapsulates formal and informal learning through exposure to globalization. Current managers and technicians in the textile industry are from generation Y (Millennials) and generation Z (or iGeneration, also known as Generation Net). The latter two generations have been educated in a technological environment, with exposure to the internet and advanced processing technologies and information technologies, including big data, in the 21st century. They also have exposure to the many impacts of globalization via social media, ease of travel, and greater language abilities. The latter generations are also increasingly conscious of environmental issues and, therefore, more willing to invest in environmentally friendly biotechnologies. However, the weight of culture, the lack of control over capital and means of production, and the economic rationality of the textile plant owners impede decisions to implement new biotechnologies. Our perspective does not seek to blame owners but emphasizes education and awareness raising amongst Baby Boomer owners who could be gradually introduced to the benefits of new technologies and big data in terms. Such benefits include cost-effectiveness, image enhancement, and environment-friendliness.

4.2.5 Challenges linked to macro, meso, and micro levels

(Weerasinghe et al., 2021) discussed how big data analytics represent a challenge at the three MMM levels of the New Zealand healthcare sector in clinical decision-making. At the macro and meso levels, the dialogue was based on strategy and big data implementation, respectively. At the micro level, the talk was about data generation and use.

Big data at the macro level in clinical decision-making was seen as an issue yet to be explored but also with a low priority. At the macro level, big data is part of modern evolving technology. The participants identified its application in the clinical care context as something to be explored in the future. Still, participants saw the application of big data as more advanced in implementation in some areas of clinical care, such as precision medicine. Representations also showed that participants view health strategy as playing a key role in dealing with difficulties in using big data, such as data quality.

Therefore, macro-level organizations are investigating the use of evolving technologies to improve care delivery. They highlight that they are continuously looking for new technologies that will positively change the model of care. Precision medicine is one such technology and is of growing interest to the government. As previously described, precision medicine provides individualized care instead of generic care. Precision medicine is also predictive; understanding a person's genomic makeup and medical history can predict a patient's future health status.

Data quality and accuracy are huge problems and barriers to implementing big data and analytics in healthcare. However, participants pointed out that the New Zealand Health Strategy now ensures: connected information, a well-defined National Health Index, and an understanding of data collection settings. Therefore, the New Zealand health strategy is expected to improve the accuracy and quality of big healthcare data that will later be used for big data analytics to make clinical decisions, undertake population health analytics, or achieve and measure health outcomes. Another important finding of this big data study was the potential for the internet of things, with its ability to capture data from devices at clinics and hospitals and remotely through wearable patient devices. Policymakers seem open to the concept of internet of things and its use to capture big data to improve clinical decision-making. However, the authors are not aware of informed research or policy in this area in New Zealand.

Due to the nature of the New Zealand healthcare system and the definition of meso-level planners, funders, and implementers, there were four types of participants at this level: District Health Boards, Primary Health Organizations, university academics, and technology vendors. While we considered these four groups separate within the meso level; generally, similar representations of big data were observed. Where there was a divergence between the representations, such differences were highlighted through the discussion.

The representations of big data, specifically by District Health Boards and Primary Health Organizations, showed that they are primarily interested in realizing medical and financial outcomes. Precision medicine is a key field in which District Health Boards are interested, but less so in Primary Health Organizations. Managers and clinical leaders at the meso-level agreed that the current situation is far from realizing the full potential of big data.

The representations at the meso level were influenced by the previously implemented systems for clinical care and their operations. It was established that most

General Practice information systems do not provide a holistic view of their clinic as a health provider and business. The current most sophisticated systems available to general practitioners are just prompting systems, reminding general practitioners to take necessary action to identify cohorts of people with specific health issues. However, the meso-level Primary Health Organizations participants argue that the starting point for big data in primary care. The government must put more effort into primary care to succeed in health-sector-wide big data approaches.

However, participants also claimed that there are improvements to tools and new tools being implemented for clinical decision making although they are not big data tools. As explained by a clinical director, a national project in New Zealand on population health uses genomics information and is likely to use big data technologies. These tools are available to doctors and can be used for clinical decision-making—however, only those interested in information technology volunteer to participate in these initiatives.

Although participants highlighted that most clinicians are unaware of the potential of big data analytics, it was clear to the meso-level participants that clinicians want better systems and better data to improve patient point-of-care service. They are advocating the need for this. Therefore, if the clinicians showed positive results, they would be the first to support big data analytics tools for clinical decision-making.

Participants state the importance of planned systems and accurate data for better clinical decisions. Getting access to information seems to be a problem across the healthcare system. Participants in information technology roles emphasized the need to provide better access to data to enhance clinical decision-making tools. Meso-level participants understand that big data analytics will bring great opportunities for better clinical decision-making tools. In addition, having better decision-making tools could help managers make better use of the workforce, as even those with lower levels of experience or qualifications can make the right clinical decisions.

Another key area of interest at the *meso* level is patient-generated data that devices used by patients can capture. Thus, participants identified patient-generated data as the source of truth and are seen as revolutionary for the current healthcare delivery practice.

However, utilizing patient-generated data is at the bottom of the priority list within the healthcare system, as there are many other priorities to achieve with big data at the population level.

At the micro level, representations showed that most clinicians do not see the same level of value from system-generated advice as other levels. They have trust issues resulting from experience with systems containing bad data (e.g., unreliable, low quality, inaccurate data) followed by medico-legal issues. Decisions are based on raw data at the point of care for general practices and hospitals. However, doctors understand that anecdotes are not the best form of medicine and hence see the importance of data for clinical decision-making. However, it was emphasized that they must ensure the data is of good quality. Manual decision support tools are available that require clinicians to record and calculate to act on urgent issues manually. The doctors see this as problematic as relying on a busy clinician to check things manually and act on them is dangerous.

Both hospital doctors and general practitioners understand the importance of good quality data in systems. Doctors will be reluctant to use data in which they have no confidence. In their view, tools that will aid clinical decision-making must have a similar testing process as pharmaceuticals going to market because although such innovations may be theoretically correct, they must first be tested in practice. Clinicians explain that people outside of clinical areas, although working in the health sector, do not understand why clinicians are mindful and hesitant about using data and tools for clinical decision-making. Clinicians suggest their work environment and professional responsibilities differ as they must deal with the consequences (medico-legal constraints) if something goes wrong. Patients do not have to undo buttons; it could be fatal if a system makes an error and the clinician acts on it. Thus, doctors always question the quality of data. All this questioning and reluctance to use systems for clinical decision-making comes down to patient safety and ensuring nothing goes wrong. A simple example provided by a clinician was a prescribing system giving a fatal dose at a pediatric ward without accounting for the fact that the patient was a child. They have reasons to question the accuracy of decision-making tools in practice.

Clinicians in hospitals see the benefits of information analysis for hospital management, especially for measuring outcomes, although not so much for clinical decision-making. However, they point out that their medical training does not include training around information analysis, although it could benefit their roles. General practitioners saw clinical decision-making tools as impractical due to the nature of consultations. An older doctor claimed that consultations are given in a short time, and using any tool in this timeframe is difficult.

General practitioners also talked about patient-generated data and thought it was a good way to get to know the patients better, as the patients themselves can record data about their health with greater frequency (e.g., seven consecutive readings of blood pressure done at home versus one reading at the clinic) and share it at the consultation. However, micro-level participants claimed that most of the apps that patients use are apps that are made for a different market and may be problematic when used in New Zealand due to the standard funded 15 min medical consultation. Another general practitioner highlighted an issue, saying doctors do not work 24/7 in the general practitioners' practice. If a patient record was shared with him on his mobile, he does not want to look at it when he is not working, and this could potentially be life-threatening to a patient.

4.2.6 Challenges linked to management

(Raut et al., 2021) identity twelve significant barriers against big data analytics implementation in Indian manufacturing supply chains. The first one is poor data quality and lack of trust in data. Data is intangible, and measuring its quality is a multi-dimensional problem. Poor data quality is a big barrier to analytics activities and significantly affects management's decisions. The data quality can be categorized into two dimensions: intrinsic (completeness, consistency, timeliness, and accuracy) and contextual (data reputation, accessibility, believability, quantity, value-added, and relevancy). It may be noted that the trustworthiness of the data obtained from social media is a serious issue.

The second one is a time-consuming activity, predictive analysis is a time-consuming initiative and comprises various development, testing, and adoption phases. It is a long task to bring experts together from different sections with different mindsets. It may be noted that top management's commitment is required to implement big data analytics, which may take one to one and a half years. Also, collecting data from various sections of the organizations, combining, validating, and cleansing the same, and tracking the development together constitute a tedious activity. The third one is the lack of sufficient resources. In a supply chain network, the resource capabilities of the data and analytics vary significantly across organizations. Lack of sufficient information technology capabilities for sharing information and data can cause considerable differences. Forming cross-functional teams and collaboration between the various elements within the firm is necessary to implement big data analytics effectively. However, while forming the team, issues such as policies of data sharing, arrangements of incentives, etc., need to be taken care of. Fact-based management and data-driven culture need to be motivated to utilize big data analysis and business value creation efficiently.

The fourth one is the lack of security and privacy. There are various issues associated with the big data analytics systems implementation, i.e., ineffective data processing, unethical usage of data, security, and privacy, which could influence the final results of the investigation. The fifth one is the lack of financial support. Lack of financial support influences the big data analytics implementation decision significantly. It may be noted that supporting and leveraging the capability of cloud computing for storing the data could add cost to the firm. Data generation demands more cloud space, increasing the organization's financial burden. Big data analytics implementation may lead to behavioral issues like over and underestimation due to real-time data and information availability. Over and underestimation refers to any deviation from the standard operating procedure. This may lead to increased inventory costs and supply chain risk. The employee may also fear job loss due to technology upgradation. These behavioral issues may sometime result in the acceptance of statistically significant and unconnected correlations. Ambiguity and unclear benefits on return on investment make stakeholders reluctant to implement big data. Further, fear of big data analytics implementation failure results in a loss of confidence to recover the investment made. The eighth one is the lack of top management support. The top management leadership should leverage and support big data analytics across the firm, as big data analytics implementation can improve the overall performance of the supply chain. Lack of motivation from top management results in low momentum for big data analytics implementation.

The nineth one is a lack of skills. A recent investigation has highlighted that a lack of experts in the big data domain is a significant issue. The data scientist needs to have expertise in both analytical and domain skills. Due to insufficient professional skills, there could be an inability to identify appropriate data and develop adapted models. Data scalability refers to the ability or capacity to accommodate a change in data size using extra resources. It is often observed that data size keeps on increasing with time. After a particular period, the firms must dump their data to store newly generated data. For tackling the scalability issues, cloud computing capability may be considered. Lack of efficient techniques or procedures leads to poor quality of obtained data. In big data analytics implementation, lousy data quality is a big problem. The last one is a lack of data integration and management which is the organization's capability to utilize the techniques and tools for "collecting, integrating, transforming, and storing data from various data sources." Due to the complex nature of big data, conventional database management systems such as RDBMS are incompatible. Therefore, cloud-based or web-based electronic data interchange systems may enhance the data integration capability. The integration capability improves responsiveness and visibility.

4.2.7 Challenges linked to system, organizational, and individual levels

Public organizations generate huge amounts of data but are often unlikely to use it to gather valuable insights or transform services. (Pencheva et al., 2018) present the challenges to the adoption of big data in the public sector. They adopt three analysis levels: system, organizational, and individual. System-level barriers are understood to arise from the networked nature of big data itself, impacting the technology's adoption. They are challenges not specific to an individual public sector organization but rather those that generally hinder development across government. Based on the literature, several interrelated challenges can be identified at this level regarding privacy and security, data governance, and ethics. These issues are discussed at length in the literature but are often referenced in passing across most papers as a sober reminder of the potential limitations.

Big data presents some challenges applicable to both public and private organizations. Fundamentally, it elevates the concern about personal and organizational privacy. Analyzed and collected data often contains individually identifiable information – i.e., big metadata – that, even when anonymized, could be attributed back to users. Without robust data governance principles that establish the purpose of collecting data and the principles for its (re) use, it is possible to connect seemingly unrelated data points to grasp important information and even an individual's identity without their consent. Consent becomes a muddled concept in the Big Data age as 'it is not easy to opt-out from a dataset, and opting out might identify a person. To that end, many observers highlight the challenge of establishing legislation to address these complex eventualities. Intricately related is the question of ethical use.

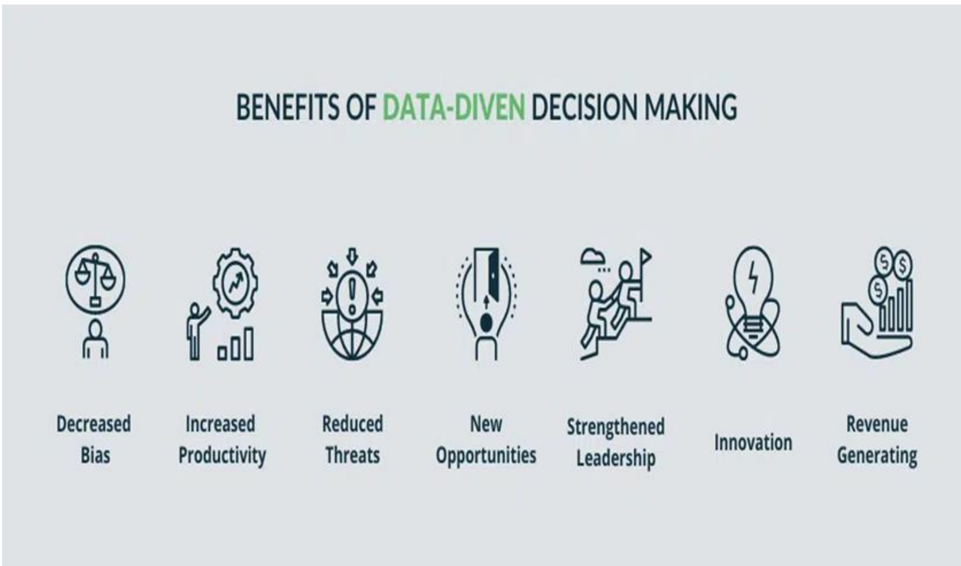
Several factors within the public sector intensify these systemic issues. First, due to their mandates, public agencies collect vast swathes of sensitive information on citizens, ranging from healthcare records to social benefits. These, if used together, could elucidate an almost complete picture of the individual's life, significantly undermining privacy. Second, organizations can collect only the data needed to fulfill their missions. In government, where mandates are often unclear, unstable, and subject to multiple interpretations, having clear purpose limitation rules becomes even more problematic. Third, there are wide-ranging, often dystopian speculations around the ethical use of big data in government. Suppose sophisticated predictive models can be used to forecast crimes before they happen. Would it be just or equitable to use this information in probabilistic policy-making to pre-emptively punish potential offenders. Some sceptics argue that big data in the public sector could lead to mass surveillance and an Orwellian state monitoring of citizens. For example, real-time censoring techniques and analytics on policy preferences have been used in China to identify and warn policymakers of potential salient issues and political unrest. Finally, regarding security, public organizations have become a regular target for cybercriminals due to the valuable data transacted. In the Big Data world, this threat would be even greater.

The second type of barrier that impacts the adoption of big data in government is organizational-level constraints around collaboration, resources, and skills. Data creates unique challenges for collaboration in the public sector for several reasons. First, the lack of policy and regulatory frameworks to guide and promote collaboration. Public managers view poor data governance across organizational boundaries as a significant barrier to adoption. From an operational perspective, the relatively siloed approach within which many public sector organizations operate causes various issues, from the technical interoperability of IT systems to the lack of comparable data parameters. It is also suggested that coordination costs associated with data-sharing may be greater than other types of collaborative endeavors in the public sector. It is argued that turf wars might significantly hinder data sharing across bureaucratic organizations. Suggesting that big data is used by agencies as a weapon to fight over funds, influence, and autonomy, and references the arguments of the American Government Accountability Office that the continuous refusal of agencies to share their big data is one reason why US exports are not as competitive as they can be.

More generally, organizational culture and inertia in some public sector organizations are also seen as limiting the adoption of new strategies to derive value from data. Simultaneously, election cycles and the resultant changes to the political authorizing environment could also impact the momentum and pace of big data transformation. From an operational standpoint, there is a relative lack of resources and skills within public organizations to implement big data solutions effectively. Government bodies have a dubious record on the guardianship of large-scale datasets, the management of contract relationships and large technology-based projects, and the capacity to innovate with newer media and technologies compared to firms, third-sector organizations, and citizens. Hence, they also lag in big data, although this situation is changing with technological advancements in developing data-driven solutions for policymakers.

Finally, a few barriers at the individual level are noted in the literature, but relatively little attention is paid to these. The main challenges in this area are identified for those public managers and policymakers with decision-making power. Particularly, the attitude of public managers toward risk is an important factor whereby more risk-averse individuals might be less likely to adopt and utilize big data effectively.

4.3 Implication



As seen from the users, big data augment decision-makers in various sectors. Yet its implementation remains a big challenge. As a result, decision-makers not yet implementing big data face a negative impact on their performance. Big data non-users rely only on themselves for decision-making, which makes it difficult, especially in the recruitment hiring process. Poor hiring practices negatively impact a company because finding high-performing candidates takes time and resources. When a company uses big data in human resources, it can make these processes more efficient and effective. They again face a negative impact on their efficiency. Any professional knows how important it is to keep costs down wherever possible. Leveraging big data can provide more cost-cutting opportunities. Netflix, for example, uses big data to save around $1 billion annually on customer retention alone. Big data non-users poor handle competitiveness. They cannot use big data solutions to increase their productivity levels. Analyzing more data more quickly can speed up other business processes and increase productivity more broadly throughout, hence giving a hedge over competitors. Big data analytics also provide customer service departments with myriad data-driven insights, allowing managers to measure employee performance and overcome shortcomings. Because companies have access to a wealth of information through big data, it's no surprise that many will use it to serve their customers better, thus developing better competitiveness. As overall, Big data non-users do not contribute to the digital economy.

5. Recommendations

A proper deal with challenges faced with big data should be adopted. It is important to first understand the term AI and its role in decision making. AI in the era of big data acts as decision support, that is a tool that increases decision makers skills not an automation of decision making to replace them. And that decision makers needs to be in constant learning since AI systems needs to always be upgraded that is refined and improved to boost its performance in assisting decision makers in the era of big data. One of the best ways to handle challenge is to either personally get skills through learning about how to sort it out and act accordingly or to hire a skilled person to fix that on your behalf. To the challenges of big data linked to reliability, quality, and structure, for example, data engineers are welcome to handle that.

More awareness of big data usage in decision making in terms of its benefits and challenges should be advertised. This will help non users to adhere and users to become more confident towards big data. This will contribute in boosting digital technology as more sectors will get big data involve in their decision making and with time none will be left out regarding digital technology.

6. Conclusion

Big data analytics has attracted significant attention from academicians and practitioners as it provides several ways to improve organizations' economic performance and efficiency. In the same line of thought, this study focused on big data and decision making in AI. The objectives were three folded. The first is to find out how big data has been used to enhance decision-making. The second one suggests the challenges big data non-users face when adopting big data. The last one recalls the implication of not incorporating big data as driven by decision-making. In the era of big data, significant data initiatives are critical for transforming traditional decision-makers into data-driven decision-makers, thus placing big data analytics at the top goals. Processes are being automated, which pledges to turn into a success. This study fosters performance, efficiency, and innovation through big data applications.

To map literature on big data and decision making, we used the Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P). The literature search was done to identify relevant papers published between 2000 and 2022 in the comprehensive database of Web of Science, and Scopus. Articles dealing with big data and decision making in AI were considered, particularly research papers.

According to the representation of research by sectors, during the last 7 years, research have been done most in diverse sectors and account 32%. Manufacturing is second with 27%. Then comes the health sector with 10%. Transportation, retail and finance are 7% each. Education is 5% while government, agriculture and food services are 2% each. None relevant studies are on energy and telecom.

According to the representation of research approach, empirical studies have a more significant influence on the overall publications, as it's account for 100%. The survey accounting for the highest rate (56%), followed by case study and secondary with 20% each. The result suggests more qualitative studies over quantitative studies.

According to the distribution of papers published over time, the highest number of publications is seen in 2021 with 15 papers, followed by 2019 with 10 papers. The result suggests a positive trend and alignment with the rising global concern and interest in big data and decision making in AI during the last 7 years.

According to the distribution of articles by journals, the journal, Technological Forecasting and Social Change has the highest number of publications (7), followed by International Journal of Information Management with 3 publications. A total of 41 reviewed articles were published by 27 different international journals across various sectors. This result suggests much relevance of the topic to different academic fields and for policy makers.

According to the author and co-authorship analysis, 100% of the papers were co-authored. Our institutional affiliation analysis from Table 3 shows that United Kingdom, China, and India have more affiliated institutions with 29, 28, and 12 papers, respectively. This suggests that institutions are developing more interest in decision making using big data in AI.

Big data is used to solve problem. Big data helps overcome the challenges of obtaining valuable information. Big data boost circular economy performance, demonstrating that big data analytics capability drives decision-making quality in its effectiveness and efficiency. It contributes to employees' development; it enhances and sustains performance. Big data analytics have the potential to enable innovation, thus improving innovation efficacy and efficiency. It provides the means to manage the existing data and human resources altogether. Big data assesses and provides business value. It creates agility through knowledge management and has a positive impact on the process to give competitive advantage. Big data builds competitive intelligence. Competitive intelligence process includes monitoring competitors to deliver actionable and meaningful intelligence to organizations. Big data also encourages better risk management. Big data management capabilities lead to high online quality ratings by mediating knowledge creation and service innovation. Big data is used for knowledge co-creation. Big data help to make informed decisions, recognizes customers' real sentiments, and satisfy them. Big data can help control unexpected event that can cause disruption (the case of COVID-19 and the use of health QR code to detect the location, personal information, and abnormalities); thus, it increases smart effectiveness and helps respond to market turbulence. Big data can help successfully develop a new product. Big data creates value by enhancing or validating policy.

Big data users face challenges. Big data involves a vast amount of data structuring and that decision-makers must collaborate with the right data scientists to interpret the data they collect. It implies a challenge in terms of its extraction, relevance, exploitation, and management. The challenge for decision-makers, therefore, resides in acquiring the skills necessary to extract from big data what is of most value to them and exploit it.

Misunderstanding the term AI is a challenge in big data for decision-making. Another challenge is the lack of measuring the benefit of AI and its impact. The role of AI in decision-making is, again, a challenge. Another challenge lies in the system design criteria for supporting decision-making. Refining and improving AI system performance while in use by decision-makers sounds difficult. AI users' behavior issues also count. Understanding the critical success factors affecting AI for decision-making is also a challenge. There is a lack of understanding of the synergy of AI and big data. Culture, personal values, and AI applications matter as well. Last, ethical and legal issues again matter.

Under the organization-wide challenge, we can count a lack of understanding and strategic planning. Another one is the lack of top management commitment. The third one is the lack of collaboration and alignment among organizational departments. Under people barriers, we have a lack of qualified and experienced consultants. Another challenge is the lack of in-house data scientists. The third challenge is the lack of trust in big data analytical results. And the fourth one is user resistance caused by job roles and skills changes. Under the technical and data challenge, an immature central processing system and the internet of things development exist. Another one is the lack of an integrated and consistent big data set.

Big data users also face traditional and cultural aspects in decision-making as well as the generation and education conflicts. At the macro and meso levels, issues on big data reliability, quality, and accuracy are raised. At the micro level, the issue is more on data generation or source.

Another twelve challenges arise. The first one is poor data quality and lack of trust in data. The second one is a time-consuming activity. The third one is the lack of sufficient resources. The fourth one is the lack of security and privacy. The fifth one is the lack of financial support. There are also behavioral issues. Ambiguity and unclear benefits on return on investment is also one. The eighth one is the lack of top management support. The nineth one is a lack of skills. There are also data scalability issues. Lack of efficient techniques or procedures is also part. The last one is a lack of data integration and management.

Challenges are also found in three levels. The system-level challenge is understood to arise from the networked nature of big data itself, impacting the technology's adoption.

The organizational-level challenge constraints around collaboration, resources, and skills. And the individual level challenge involves the attitude toward risk, as in whether risk-averse or risk lover vis a vis big data.

Big data users benefit from the AI advantages as big data act as assistance in decision making, as a result, it enhances knowledge, performance, efficiency, their productivity, and give a hedge on competitiveness. As overall, big data users contribute to the digital economy.

A proper deal with challenges faced with big data should be adopted. It is important to first understand the term AI and its role in decision making. AI in the era of big data acts as decision support, that is a tool that increases decision makers skills not an automation of decision making to replace them. And that decision makers needs to be in constant learning since AI systems needs to always be upgraded that is refined and improved to boost its performance in assisting decision makers in the era of big data. One of the best ways to handle challenge is to either personally get skills through learning about how to sort it out and act accordingly or to hire a skilled person to fix that on your behalf. To the challenges of big data linked to reliability, quality, and structure, for example, data engineers are welcome to handle that.

More awareness of big data usage in decision making in terms of its benefit and challenges should be advertised. This will help non users to adhere and users to become more confident towards big data. This will contribute in boosting digital technology as more sectors will get big data involve in their decision making and with time none will be left out regarding digital transformation.

The lack of availability of data (the literature) did not allow to involve big data and decision making in developing and emerging countries which constitute a limitation to this study. Hopefully in the future with more literature on it, it can be done.

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